

# Predicting User Satisfaction from Medicine Data: An In-Depth Analysis

# Objectives

- **Analyze factors influencing user satisfaction:**
  - Explore the dataset to identify key features that impact user satisfaction.
- **Predict user satisfaction Rating:**
  - Apply machine learning models to predict user satisfaction rating based on the identified features and data insights.
- **Deploy the model:**
  - Select the best performing model and deploy it using Streamlit for practical usability and user interaction.

# Data Summary

- **Dataset Overview:**

Total records: 11825

Total variables: 9

Missing values: No missing values

- **Data source:** Kaggle

\*\*\*\*\*Dataset Overview\*\*\*\*\*

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 11825 entries, 0 to 11824

Data columns (total 9 columns):

#	Column	Non-Null Count	Dtype
0	Medicine Name	11825 non-null	object
1	Composition	11825 non-null	object
2	Uses	11825 non-null	object
3	Side_effects	11825 non-null	object
4	Image URL	11825 non-null	object
5	Manufacturer	11825 non-null	object
6	Excellent Review %	11825 non-null	int64
7	Average Review %	11825 non-null	int64
8	Poor Review %	11825 non-null	int64

dtypes: int64(3), object(6)

memory usage: 831.6+ KB

None

None

memory usage: 831.6+ KB

dtypes: int64(3), object(6)

8	Excellent Review %	11825 non-null	int64
---	--------------------	----------------	-------

# Analytical Approach

## ➤ Data Exploration and Preprocessing:

- Clean and preprocess the dataset, handling missing values and duplicate entries.
- Create new feature 'Rating' based on review percentages.

$$\text{Rating} = ((5 * [\text{'Excellent Review \%'}] + 3 * [\text{'Average Review \%'}] + 1 * [\text{'Poor Review \%'}])/100)$$

## ➤ Understanding Features:

- Analyze the data through visualization and understand the relationship between different features.

## ➤ Encoding techniques:

- Apply encoding techniques to convert categorical features into numerical form.

## ➤ Feature Engineering and Target Set Creation:

- Create a feature and target set for prediction by selecting relevant input variables and defining the target variable.

## ➤ Train-Test Split:

- Split the dataset into training and testing sets.

## ➤ Apply Machine Learning Techniques:

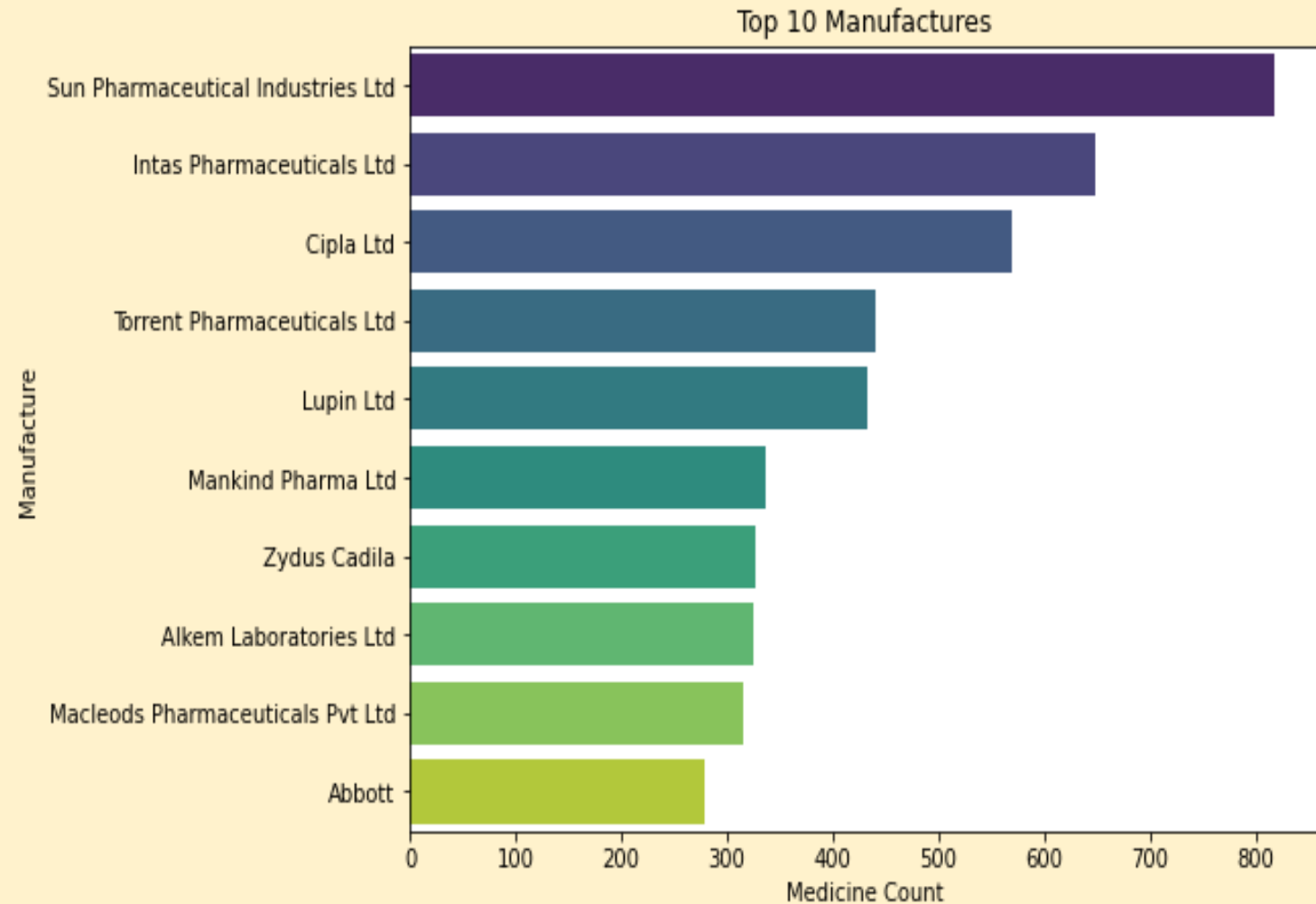
- Apply machine learning techniques to predict user satisfaction and compare performance of different models based on metrics like MSE and R2.

## ➤ Deploy the best model:

- Select the best-performing model based on evaluation metrics and deploy it for future predictions.

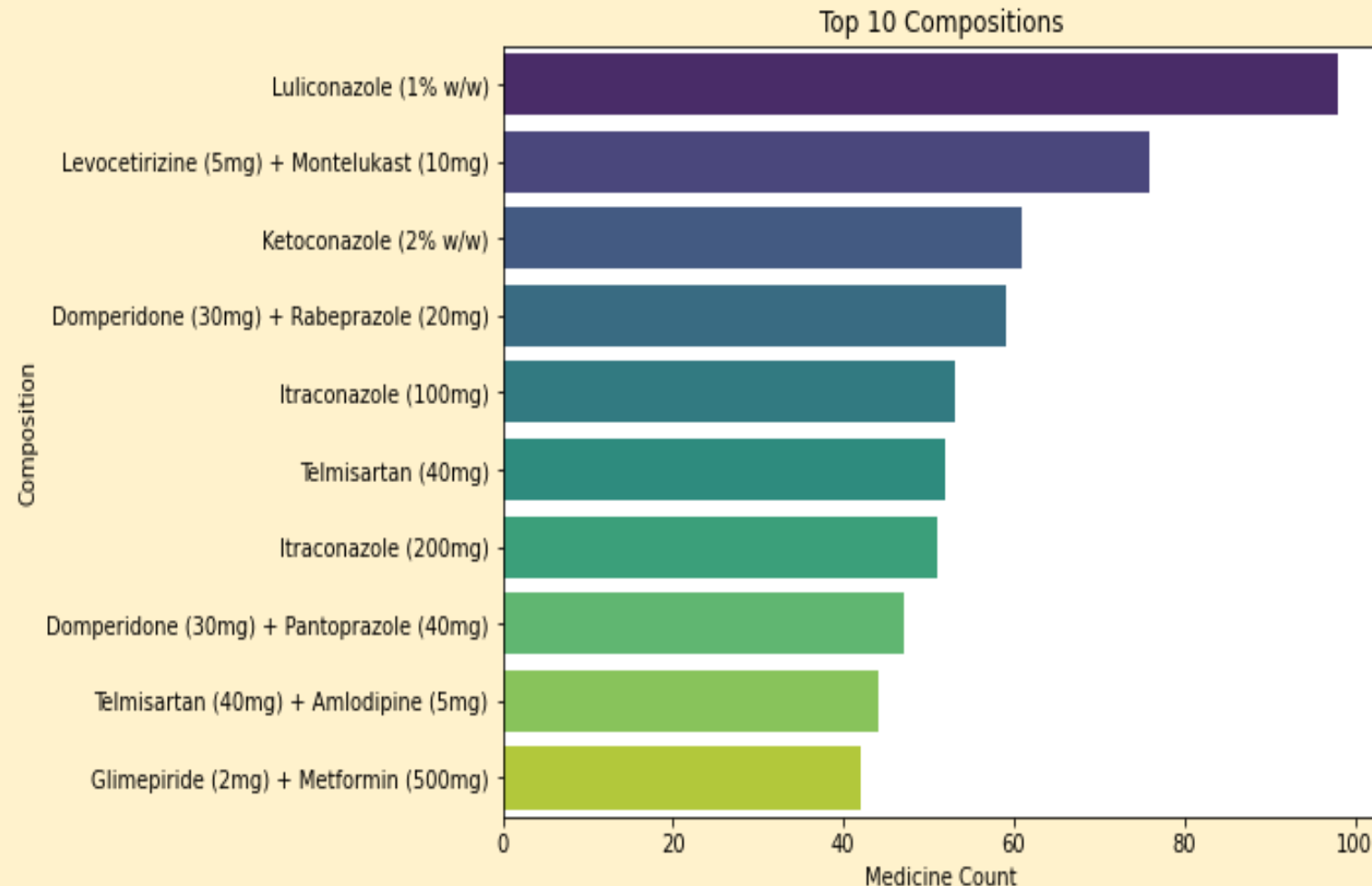
# Top 10 Manufactures By Product Count

- ❑ **Sun Pharmaceutical Industries Ltd** has the highest product count of 819.
- ❑ **Intas Pharmaceuticals Ltd** follows with 648 products.
- ❑ **Cipla Ltd** ranks third with 569 products



# Top 10 Compositions

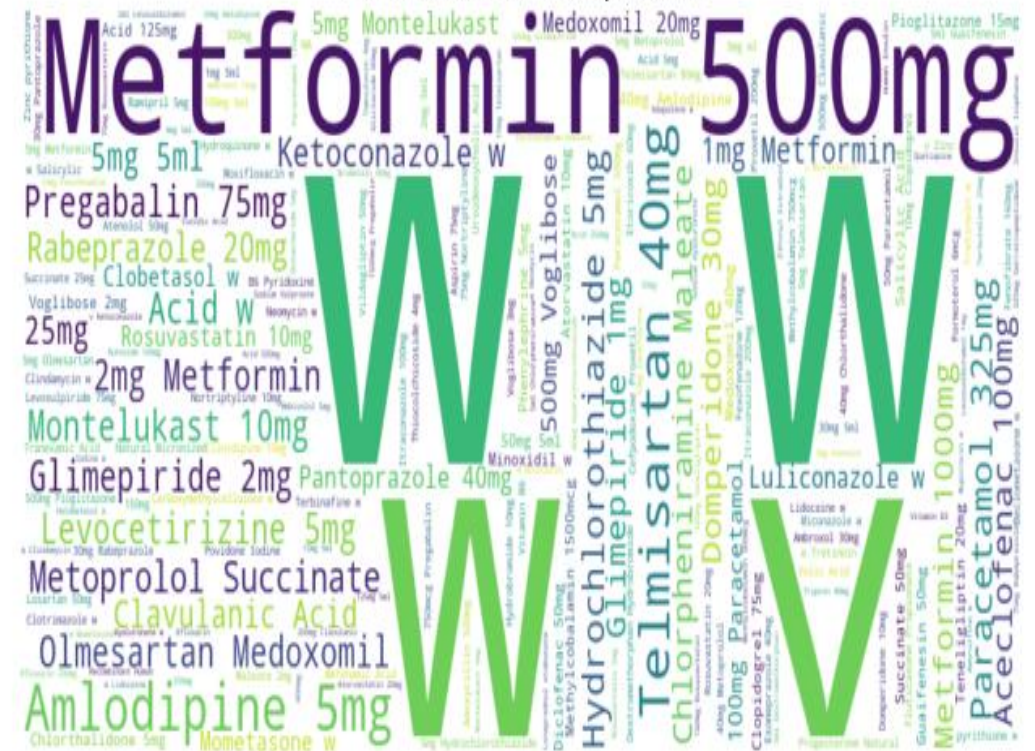
- ❑ **Luliconazole (1% w/w)** appears in the highest number of medicines (98 products).
- ❑ **Levocetirizine (5mg) + Montelukast (10mg)** is the second most common composition, found in 76 medicines.
- ❑ **Ketoconazole (2% w/w)** and **Domperidone (30mg) + Rabeprazole (20mg)** are present in 61 and 59 medicines, respectively.



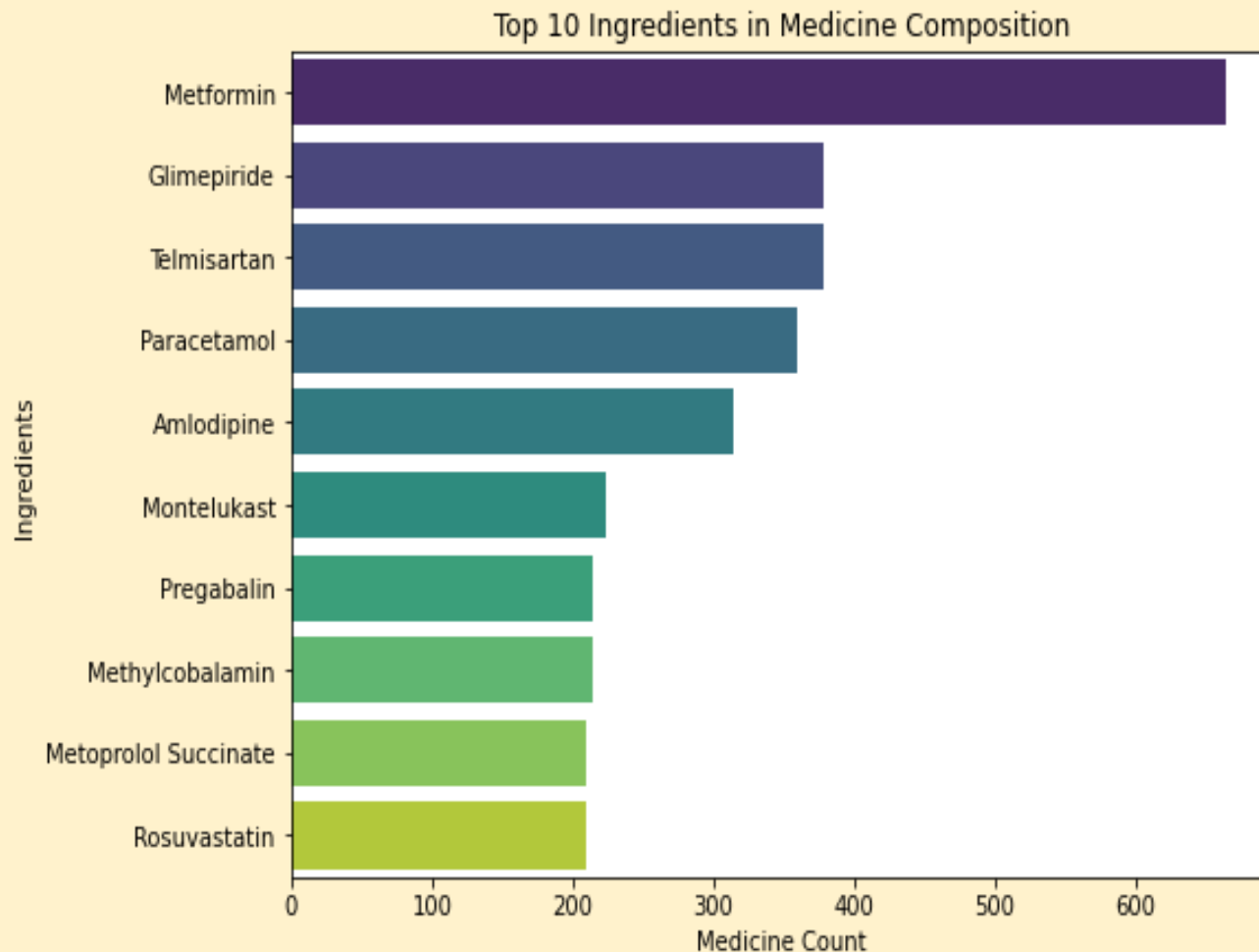


# Word Cloud For Composition

Word Cloud for Composition



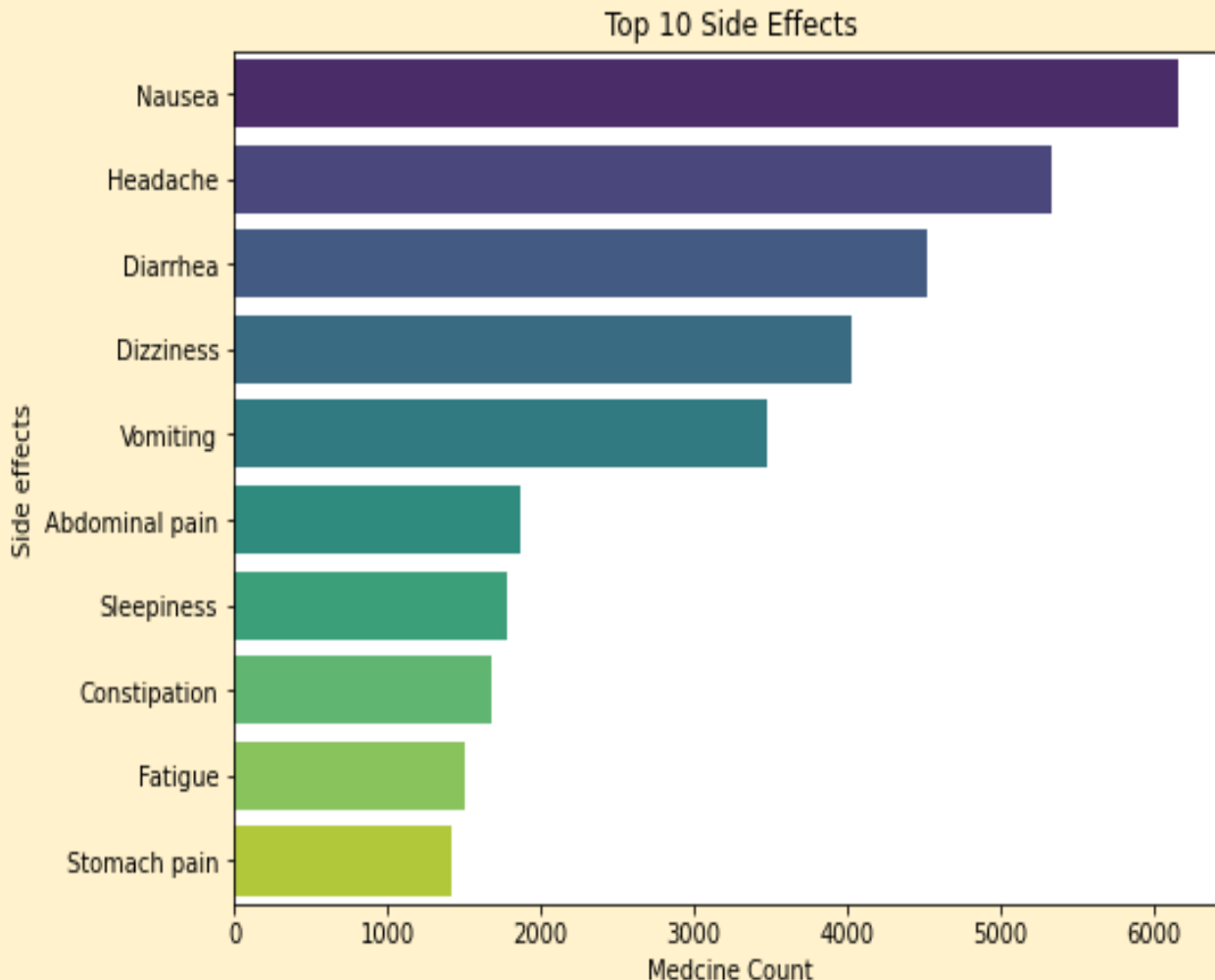
# Most Commonly Used(top 10) Ingredients In Medicine Composition



- ❑ **Metformin** is the most common ingredient, present in 664 medicines, commonly used for diabetes management.
- ❑ **Glimepiride** and **Telmisartan** are the next most frequent ingredients, appearing in 379 medicines each.
- ❑ **Paracetamol** ranks fourth, found in 359 medicines



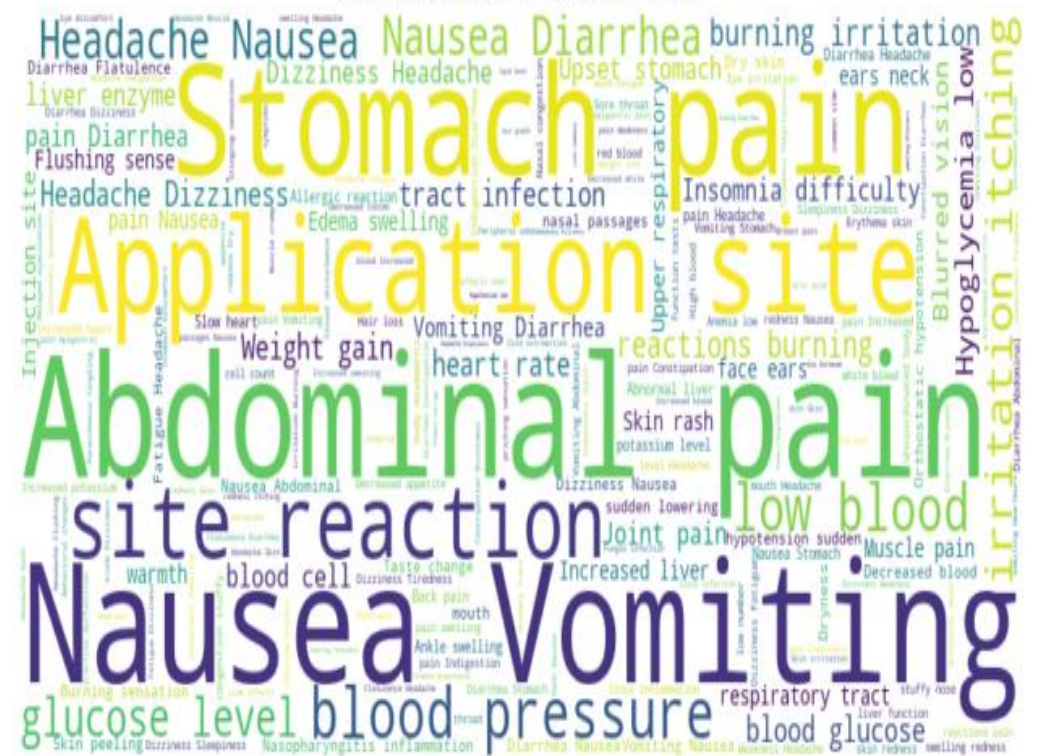
# Top 10 (Most Common) Side Effects



- ❑ **Nausea** is the most frequently reported side effect, found in **6,170** medicines.
- ❑ **Headache** occurs in **5,336** medicines, making it the second most common side effect.
- ❑ **Diarrhea** is reported in **4,520** medicines.

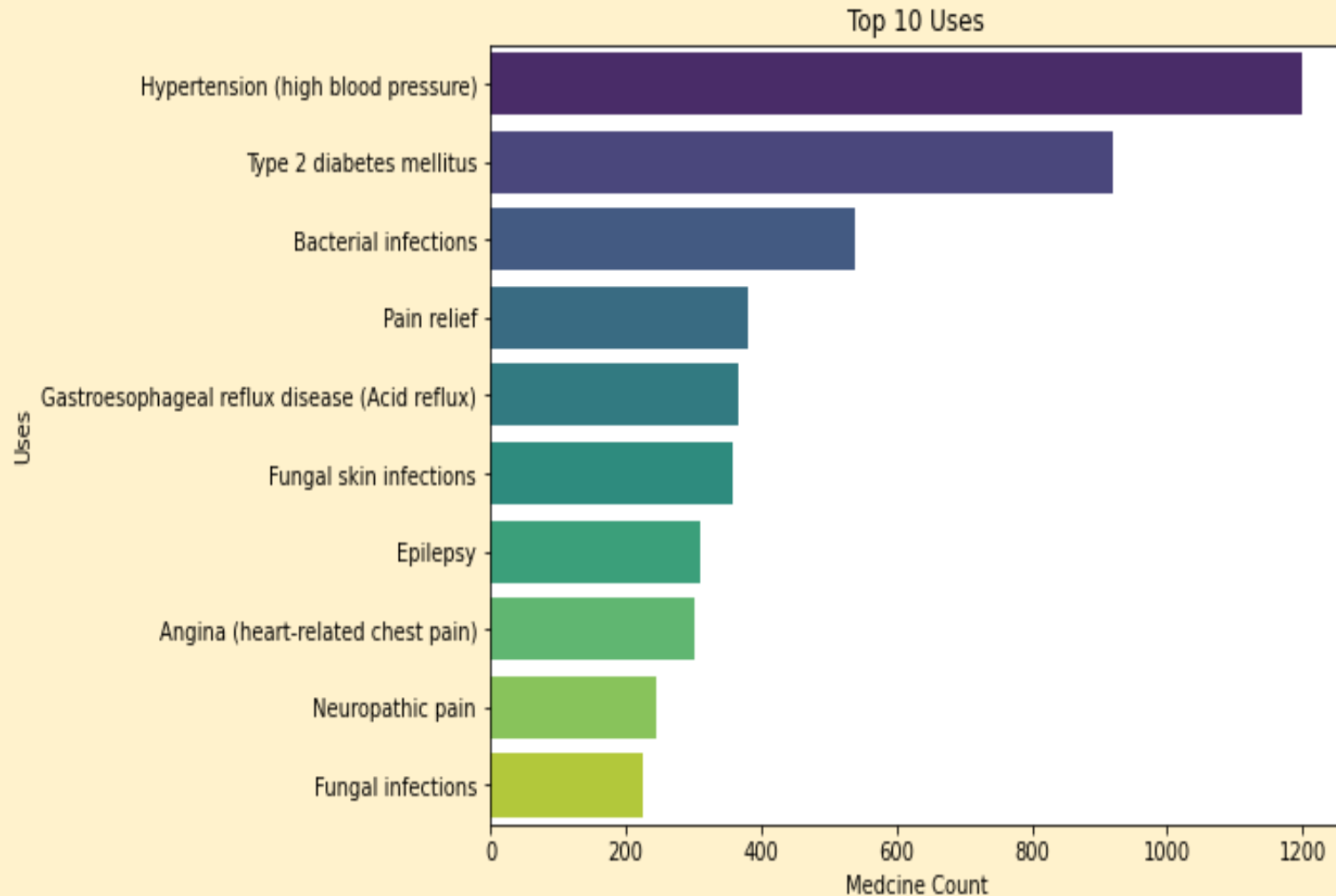
# Word Cloud For Side Effects

### Word Cloud for Side effects



# Top 10 Uses

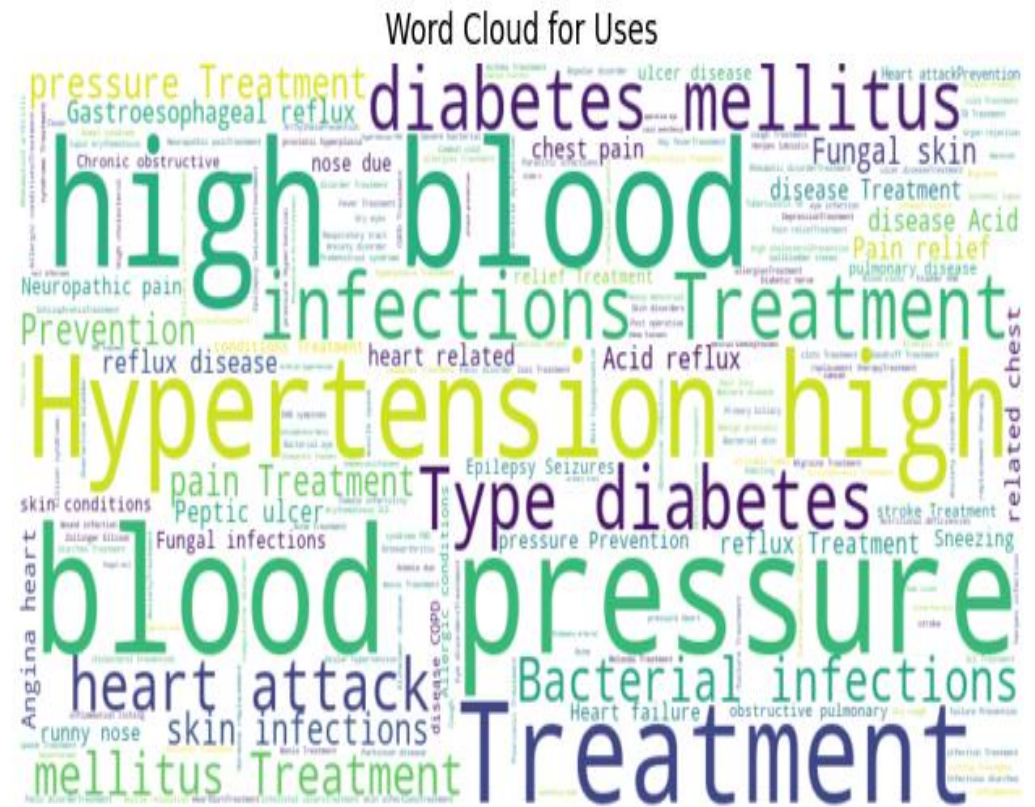
- ❑ **Treatment of hypertension (high blood pressure)** is the most common use, with 1200 medicines used for this condition.
- ❑ **Treatment of type 2 diabetes mellitus** is treated by **920** medicines.
- ❑ **Treatment of bacterial infections** are third most common use, with **540** medicines used for this condition.





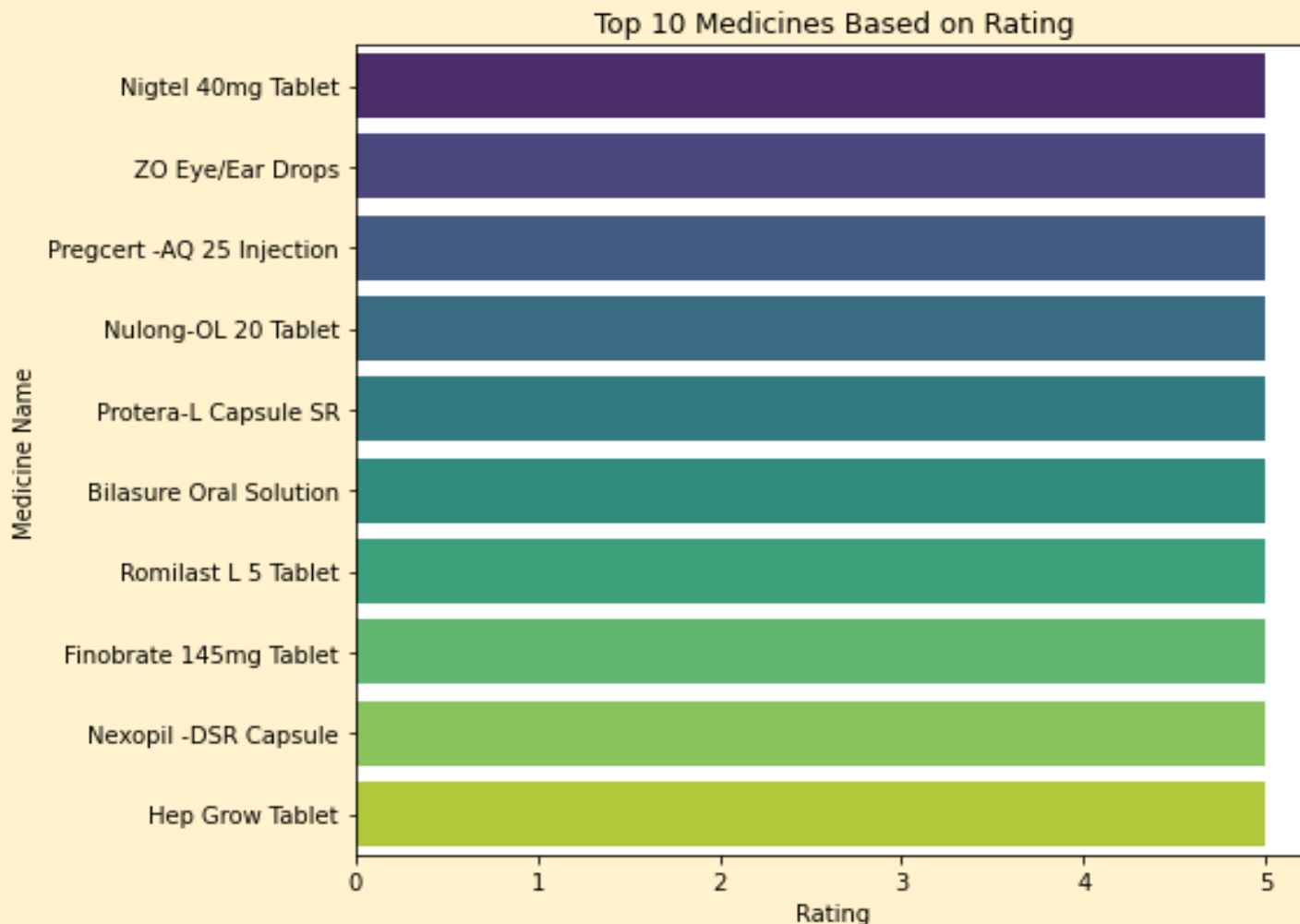


# Word Cloud For Uses



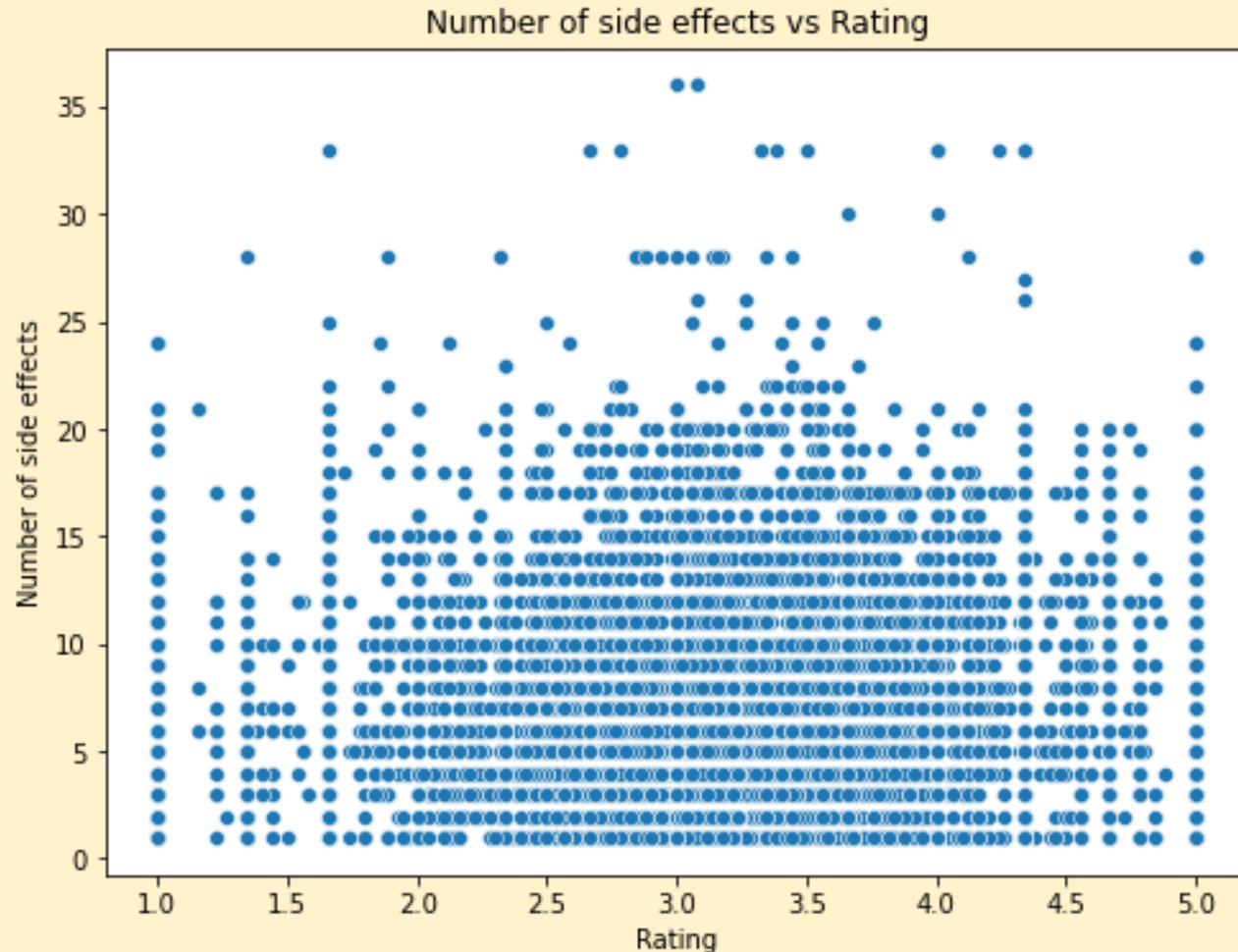


# Top 10 Medicines Based On Rating



Top 10 medicines with rating 5 includes Nigtel 40mg Tablet, ZO Eye/Ear Drops, Pregcert -AQ 25 Injection etc.

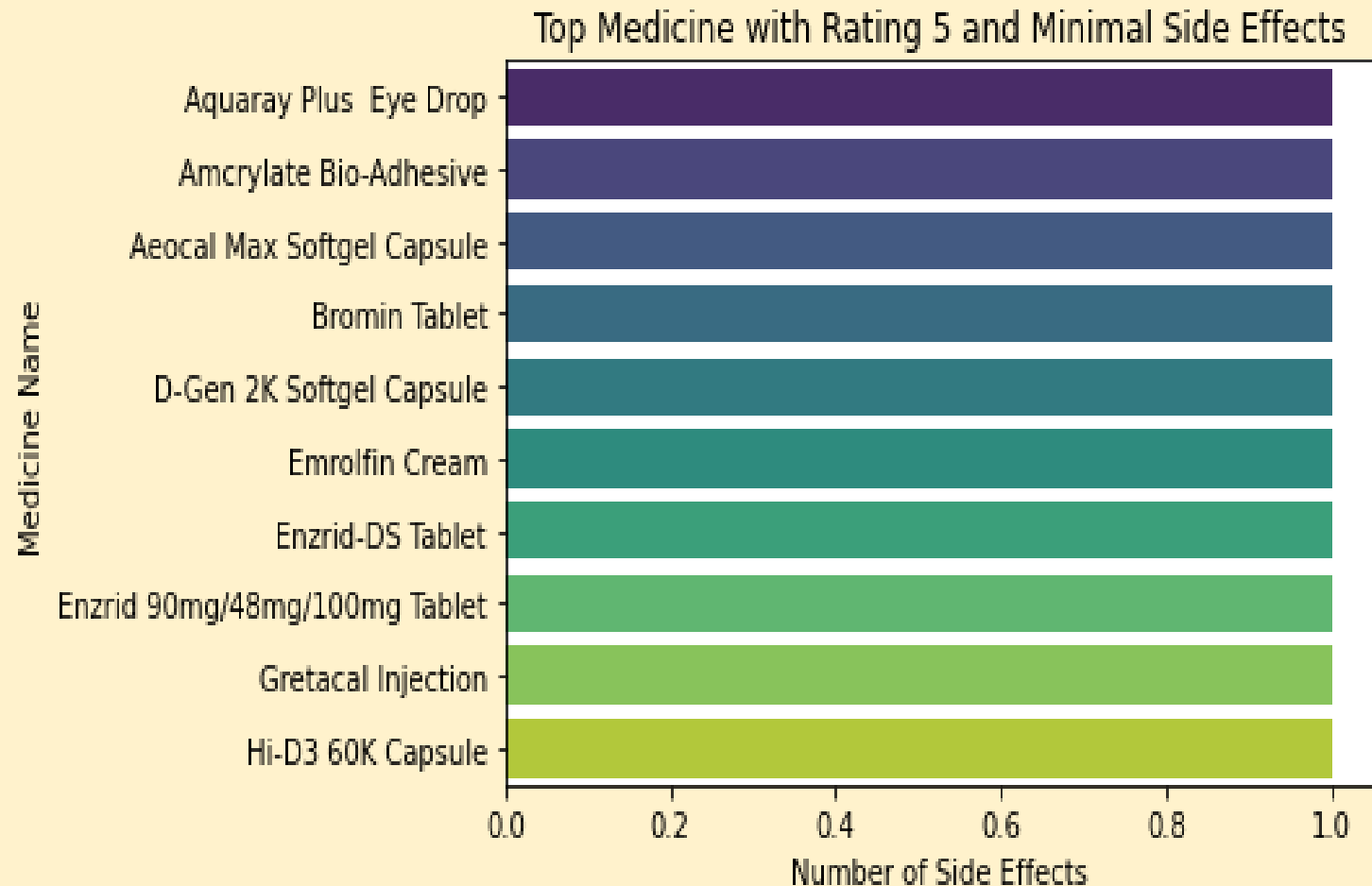
# Number Of Side Effects Vs Rating For A Medicine



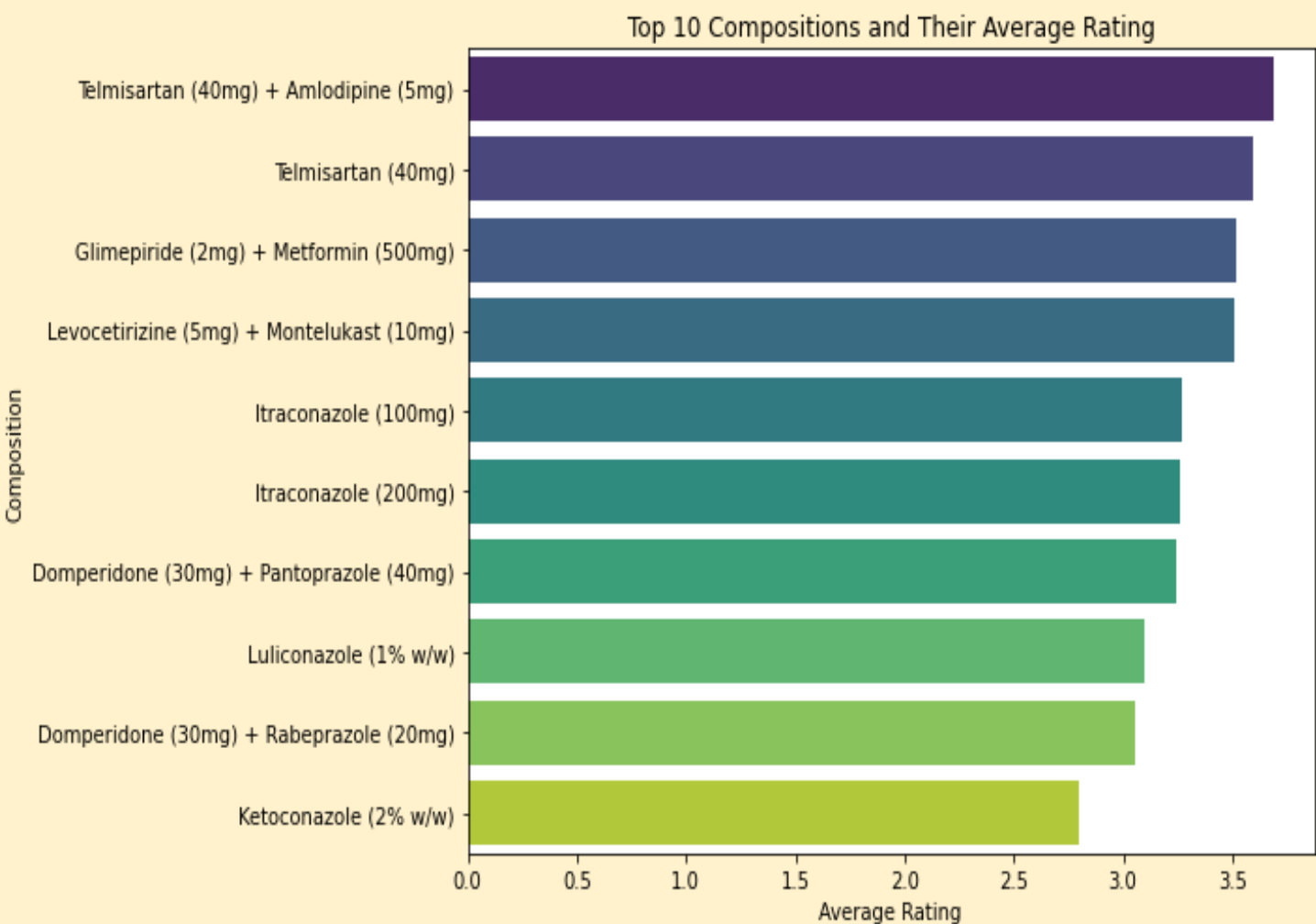
- ❑ There is no clear or consistent correlation between the number of side effects and the rating.

# Top 10 Medicine with Rating 5 and Minimal Side Effects

- ❑ The top-rated medicines (rating 5) with fewer side effects includes, Aquaray Plus Eye Drop, Amcrylate Bio-Adhesive, Aeocal Max Softgel Capsule etc.
- ❑ All these have rating 5 and side effects less than 2.



# Top 10 Compositions And Their Average Rating

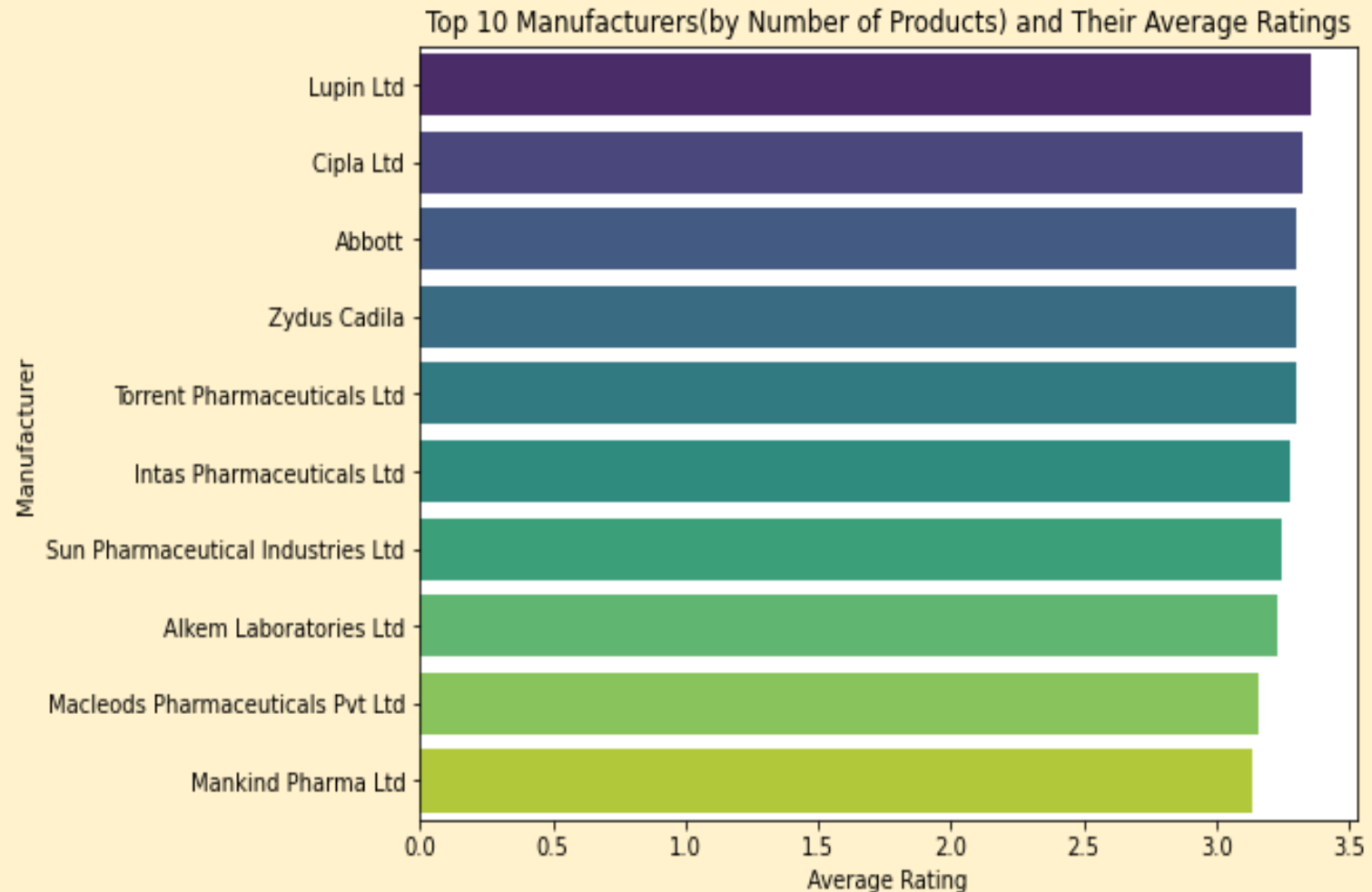


- ❑ **Telmisartan (40mg) + Amlodipine (5mg):** Composition with highest average rating, 3.69
- ❑ **Telmisartan (40mg) :** Composition with second highest average rating ,3.59
- ❑ **Glimepiride (2mg) + Metformin (500mg):** Composition with the third-highest average rating, 3.52

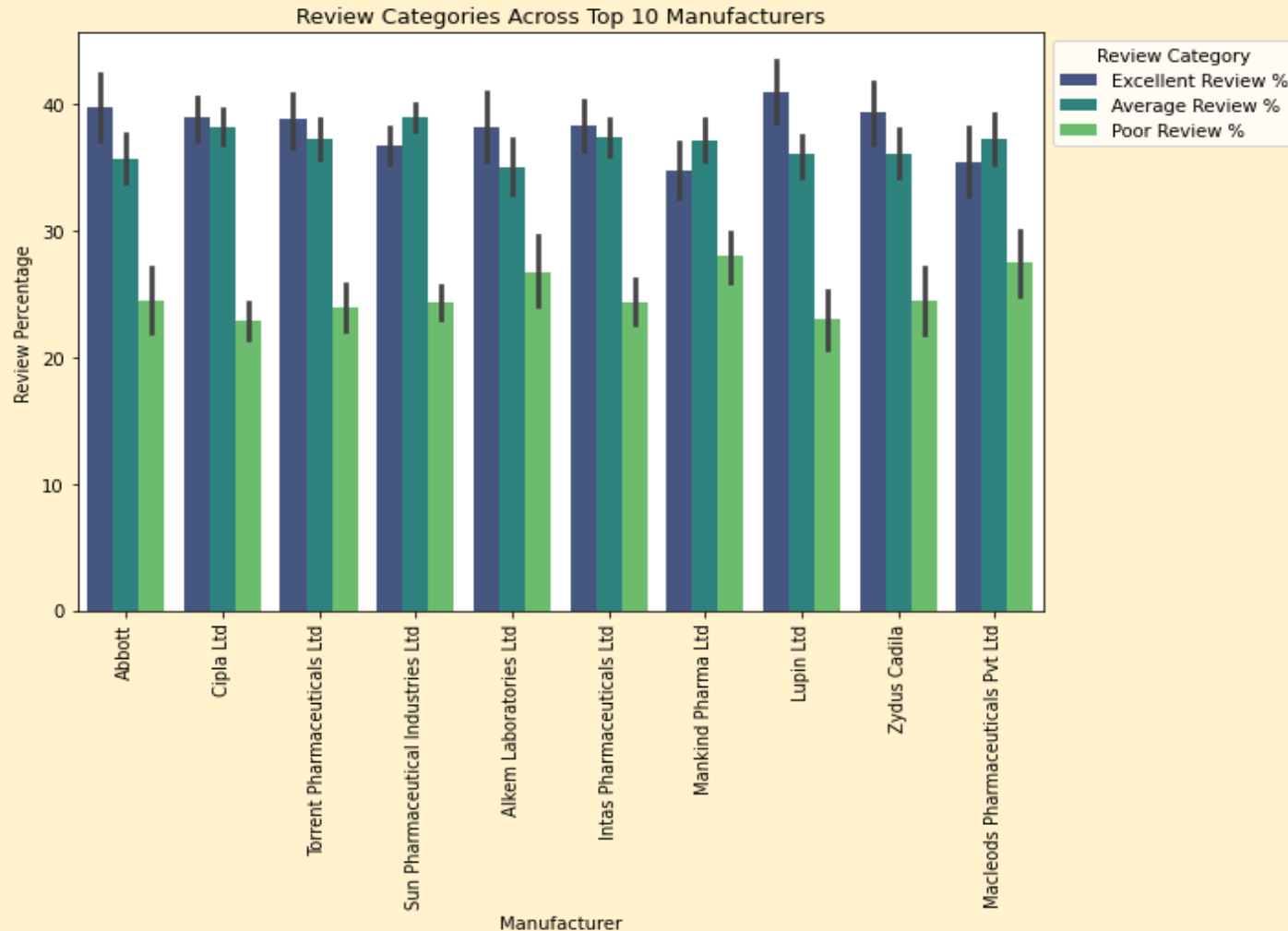


# Top 10 Manufactures(Based On Number Of Products) And Their Average Ratings

- ❑ **Lupin Ltd:** Manufacturer with the highest average rating, 3.36
- ❑ **Cipla Ltd:** Manufacturer with the second-highest average rating, 3.32
- ❑ **Abbott:** Manufacturer with the third-highest average rating, 3.30

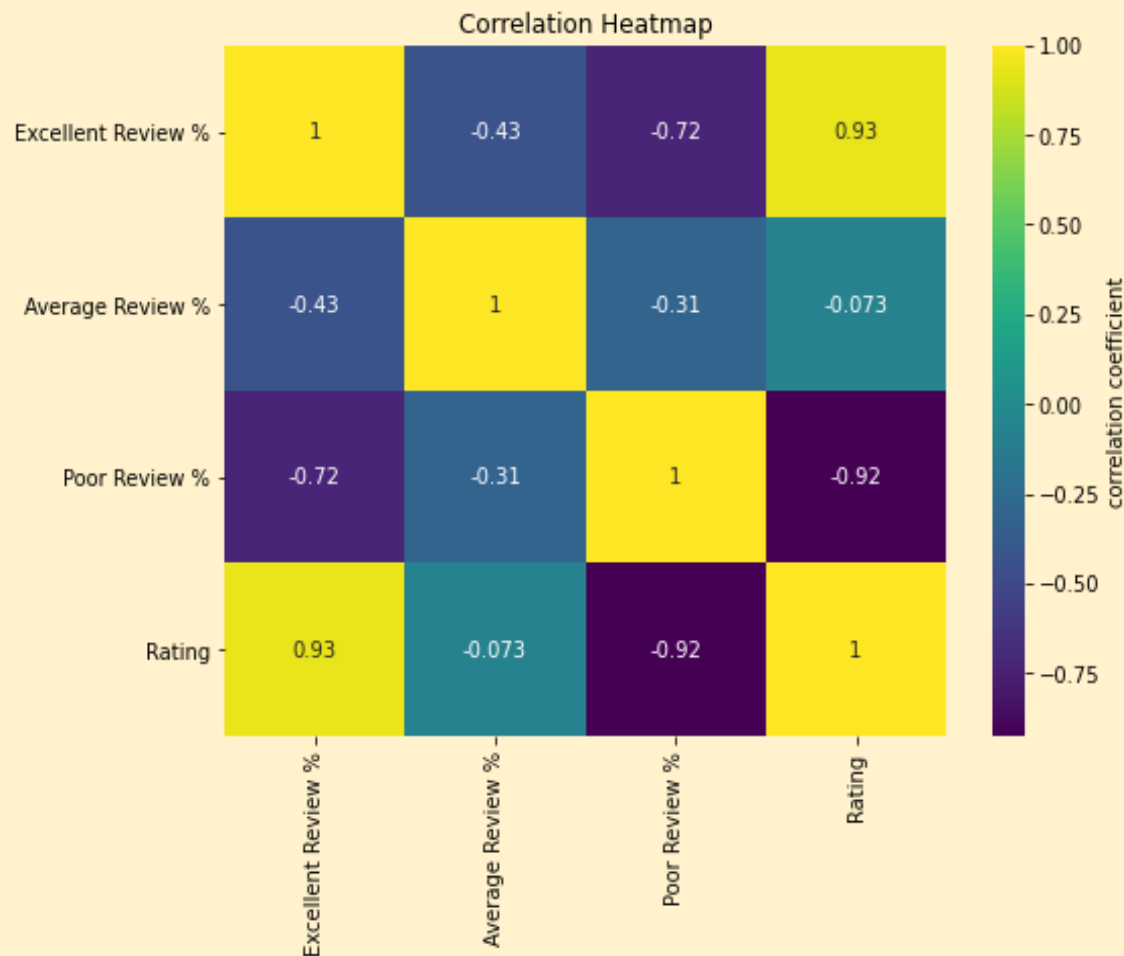


# Review Category Of Top 10 Manufactures (Manufactures With Highest Number Of Products)



- ❑ All top manufacturers have a higher proportion of Excellent and Average reviews compared to Poor reviews.
- ❑ **Lupin Ltd:** Manufacturer with the highest proportion of excellent review, suggesting a strong positive perception of their products among consumers.
- ❑ **Abbott:** Also has a notably high percentage of Excellent reviews.

# Correlation Between Excellent Review, Average Review, Poor Review, Rating



- ❑ **Excellent Review % and Rating (0.93):** A strong positive correlation exists between Excellent Review and Rating, indicating that a higher percentage of excellent reviews tends to result in a higher rating.
- ❑ **Excellent Review % and Poor Review % (-0.72):** A strong negative correlation exists between Excellent Review and Poor Review, suggesting that an increase in excellent reviews is associated with a decrease in poor reviews.
- ❑ **Poor Review % and Rating (-0.92):** A very strong negative correlation between Poor Review and Rating, indicating that a higher percentage of poor reviews leads to a lower rating.

# Feature And Target Set

## Feature Set

- Medicine Name
- Manufacturer
- Composition
- Excellent Review %
- Average Review %
- Poor Review %

## Target Variable

- Rating



# Encoding Techniques

## Label Encoder

- Medicine Name
- Manufacturer

## TF-IDF

- Composition

- ❑ **Label Encoding:** converts categorical values into numeric labels, simplifying the representation of data for machine learning models.
- ❑ **TF-IDF:** assesses the relevance of a word in a document based on its frequency in the document and its rarity across all documents.

# Models And Parameters

## KNeighborsRegressor

- n\_neighbors=5

## DecisionTreeRegressor

- max\_depth=3
- min\_samples\_split=10
- min\_samples\_leaf=2
- random\_state=42

## RandomForestRegressor

- n\_estimators=100
- max\_depth=3
- random\_state=42

# Model Evaluation

## Random Forest

- Mean squared error: 0.029
- R2: 0.964

## Decision Tree

- Mean squared error: 0.055
- R2: 0.934

## KNN

- Mean squared error: 0.214
- R2: 0.745



**Random Forest Regressor:** lowest MSE (0.0296) and the highest R2 (0.9647), indicating the best predictive accuracy.

**Decision Tree Regressor:** shows strong performance with a high R2 (0.9345) and relatively low MSE (0.0550).

**Kneighbors Regressor:** slightly less effective with an R<sup>2</sup> of 0.745 and a higher MSE of 0.214.

# Model Deployment

Deployed the best model  
(Random Forest Regressor)  
for real-time predictions  
using Streamlit

The screenshot shows a Streamlit web application titled "Medicine Analysis". On the left, there is a "User Input" sidebar with three sliders: "Excellent Review %" (0 to 100), "Average Review %" (0 to 100), and "Poor Review %" (0 to 100). Each slider has a red dot indicating the current value. On the right, there are three text input fields labeled "Medicine Name", "Manufacturer", and "Composition". Below these fields is a button labeled "Predict User Rating". In the top right corner, there is a "Deploy" button and a menu icon.



# Key Insights

- ❑ **Strong Correlations:** The analysis revealed strong correlations between the Excellent Review % and Rating, suggesting that higher percentages of excellent reviews are often associated with higher ratings.
- ❑ **Impact of Side Effects:** The relationship between side effects and rating was analyzed, though it was found that the number of side effects does not strongly influence the rating.
- ❑ **Top Performers:** Certain compositions and manufacturers consistently received higher ratings, with Telmisartan (40mg) + Amlodipine (5mg) and Lupin Ltd standing out as top performers in terms of average ratings.
- ❑ **Review Categories:** Excellent Reviews and Poor Reviews showed a clear inverse relationship, where higher excellent reviews correlate with fewer poor reviews, highlighting the significance of positive feedback in user satisfaction.
- ❑ **Prediction:** Medicine Name, Manufacturer, Composition, and Review Categories (Excellent Review %, Average Review %, Poor Review %) were used as key features to predict the user satisfaction rating of medicines.



*Thank You!*